RESEARCH ARTICLE

Peak emission path of rural carbon emission in Chongqing based on optimization neural network and genetic algorithm

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The growth of industrialized agriculture has caused the problem of excessive carbon emission (CE) in animal husbandry and rural agriculture. To maintain energy conservation and carbon reduction in rural economic development, this study explored the peak carbon emission path in Chongqing, China through the optimization model of back-propagation neural network and genetic algorithm. The research analyzed the optimization direction of energy structure through the carbon emission of rural industrial composition with the aim of projecting energy use efficiency, which was achieved by weighing the financial gains from energy use against the associated carbon emissions. This study extended the direction of industrial optimization by combining the cross-variance model of genetic algorithm to explore the global optimal path through population simulation. The study also improved the adaptability of the model by iterative training method with the help of the learning process of back propagation neural network adaptive data. The results revealed that the loss function of the proposed model basically converged after 30 iterations in the test set, and the prediction accuracy of the model could reach more than 80% after 60 iterations. The fitness value of the proposed model was reduced to 0.22 × 10^{-3} after 120 iterations, while the lowest fitness value of other algorithms could only be reduced to 0.38 × 10^{-3}, which indicated that the optimization effect of the proposed model was significantly better than other methods and could effectively avoid the local optimal solution problem. The proposed model could provide an effective planning path for exploring the peak carbon emissions in the rural area of Chongqing, China.

Keywords: rural economy; back propagation neural network; genetic algorithm; carbon emissions; peak carbon emissions.

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Introduction

The significance of environmental issues has increased due to the rise in the frequency of anomalous global temperatures in recent years. The greenhouse effect, as one of the triggers of the abnormal environment, has brought the international community's attention to the issue of carbon emission (CE) [1]. The process of human economic development has simultaneously caused an excess of carbon dioxide in the atmosphere. To change the national development task into an environmentally friendly development process, some scholars have shifted the direction of environmental optimization to the study of peak carbon emission (PCE) pathways [2]. Xu *et al*. set up a standard scenario to calculate the CE output of the current industry through scenario analysis method and used the predicted development trend of the carbon reduction and optimization industry to calculate the CE changes under the scenario. However, this method had limitations in judging the influencing factors in the scenarios [3]. The method of long-term energy alternative planning system proposed by Masoomi *et al*. could flexibly face the prediction of CE data of scenarios when data was missing. The method could also present specific CE change patterns through data visualization. However, the method did not have a strong fit for dynamically changing influencing factors [4]. With the emergence of intelligent optimization algorithms, Yan *et al*. used a multilayer feed-forward neural network (NN) to predict the change of CEs from industries and the time of carbon peaking based on the carbon potential of cities. However, the learning of NNs required a large amount of historical data training to be generalizable [5]. As a class of multi-factor path exploration method, particle swarm optimization algorithm could calculate the optimal solution (OS) of the scene through the random path change of particles. However, this method might easily fall into the local OS in the actual scene exploration process. From the perspective of the regional CE structure, the CEs in rural areas of Chongqing, China are mainly composed of CEs from crops and livestock followed by residents' living expenses with the CEs of other industries being accounted for a relatively minor proportion. Thus, the optimization direction of CEs in rural areas of Chongqing, China is concentrated on industries with a high proportion.

To further analyze the data on the global climate issue, some scholars have studied the way that CE is involved in the process of industrial development. Li *et al*. developed a research method based on data statistics to address the problem of urban PCE, which explored the growth pattern of CEs through the historical CE inventory and analyzed the change trends to transform low-carbon cities in many aspects such as driving factors and industrial development. The outcomes showed that the suggested strategy had a decent prediction accuracy (PA) of CE [6]. Yang *et al*. proposed an approach based on econometric analysis for the study of carbon peaking in industrial scenarios. The method compared the CE factors of different development stages statistically and numerically by analyzing the energy structure of the industrial environment in a single-factor analysis. The results showed that the proposed method was ideally suited for industrial scenarios' peak carbon pathways [7]. Hussain and Lee proposed a research method based on the duopoly game model for carbon neutrality in cities, which established the relationship between CEs and energy structure through mathematical modeling and explored the path planning to reduce CEs in a carbon neutral way. The results suggested that the proposed approach had a superior predictive impact when it came to maximizing CE magnitude [8]. Guo *et al*. suggested a methodology based on statistical analysis to address the problem of carbon peaking in metal mines. The method identified technical steps for high CEs through statistical categorization of CEs from metal mines. By modernizing technology and refining the energy structure, it was able to reduce emissions. The proposed approach offered the green mine program an efficient technological route [9]. Zhao *et al*. proposed a method based on time-weighted regression model for the regional carbon peak path. The method calculated the reduction of actual CEs through carbon reduction project planning and used the relaxation metric as the basis of scenario planning to predict the carbon peaks in each region. The results showed that the proposed approach clearly affected how areas plan for carbon reduction [10].

Zhai *et al*. developed a genetic algorithm (GA) model combined with simulated annealing algorithm for the accident evacuation route planning. The method revitalized the population individuals by simulated annealing, optimized the diversity of the population with adaptive cross-probability operator, and obtained the global OS after simulation experiments. The results showed that emergency evacuation routes could be effectively planned by using the suggested strategy in many scenarios [11]. Shishavan *et al*. proposed an improved GA model based on combining cuckoo search optimization algorithm for the population detection under complex networks. The method extended the exploitation direction through dynamic monitoring of population size to reach a balanced detection of communities with modular area exploration. The results demonstrated that the proposed method had balanced global exploration capability [12]. Boughida *et al*. also proposed a GA and filter-based research method for the facial feature recognition, which extracted the facial region features of the image with Gabor filter, strengthened the facial feature recognition by optimizing the parameter range, and explored the best recognition term with parallel processing of multiple sets of features. The results indicated the high accuracy of facial recognition of the proposed method [13]. Zhou *et al*. proposed an optimized GA for the assessment of liquefaction potential of soils. The method established a baseline assessment index through multiple data comparisons and tested the model usability with the working characteristic curves of the subjects. The results showed that the suggested approach could accurately forecast the soil's potential for liquefaction [14]. Abualigah *et al*. proposed a GA based optimization process model for scheduling in cloud computing. The method enhanced the data transfer speed in the cloud through the two-domain optimization of transfer tasks and optimized the throughput of cloud computing with the transfer decision of aggregate attributes. The outcomes showed that the suggested strategy might improve job processing efficiency and accurately mimic the cloud computing transmission process [15].

GA has been used extensively in industry. However, information about its use in environmental CE prediction is still lacking. This study creatively proposed a PCE prediction model using GA and the optimal back propagation neural network (BPNN) technique to provide a reliable optimization direction for the low-carbon goals of Chongqing's rural CE industry. The adaptive change of genetic operators was employed in this study to determine the optimal threshold of the NN, thereby optimizing the prediction accuracy of the model through error reverse adjustment. The global optimal approach of CE optimization was explored through population simulation. The CE peak prediction model constructed in this study would provide theoretical guidance for the analysis of the current regional CE structure and the optimization direction for the subsequent energy structure adjustment, promoting the acceleration of the regional CE peak in the industrial structure adjustment of rural areas in Chongqing, China.

Materials and methods

Modeling of peak CE pathways in rural areas of Chongqing, China

As the country attaches importance to environmental protection projects, the task of energy saving and emission reduction is not only concentrated in urban industry, but also gradually transferred towards the rural environment [16-18]. The optimization of rural CEs is primarily focused on two key areas including animal husbandry and planting. To effectively adjust the CE industry structure in Chongqing's rural areas, the study employed the prediction of PCEs as the entry point for improving CE problems, which involved an analysis of the industrial structure of the region and a classification of the current energy consumption. As the prediction model for PCEs was based on the calculation of actual CEs and the estimation of future CEs, the total CEs in rural areas could be calculated using the CE coefficient method as follows.

$$E = \sum EC * EF \quad (1)$$

where E was the CE. EC was the consumption of the energy type. EF was the CE coefficient of the energy type. CEs could be localized by subdividing the CE categories, and the material balance algorithm was used to complete the calculation of refined CEs as follows.

$$E = \sum EC_{abcd} * EF_{abcd} \quad (2)$$

where a was the type of CEs according to the source. b was the type of energy used in the process. c was the technical method used in the process. d was the type of operating equipment in the process. Due to the different fuels used for EC, the calculation of CEs from different fuels was obtained using equation (3).

$$E = \sum_i Q_i \times C_i \quad (3)$$

where Q_i was the intensity and quantity of substance i . C_i was the fuel CE factor. Considering the presence of greenery in the rural environment to mitigate the growth of CEs, the amount of carbon sequestered by greenery was calculated as below.

$$C_{plant} = \sum_i^n Q_{ci} \times M_i \times D \quad (4)$$

where C_{plant} was used as the amount of carbon sequestered by plants. Q_{ci} was the daily carbon sequestration per unit of green plants. M_i was the area covered by green plants. D was the time unit. To express the EC in Chongqing countryside in a hierarchical manner, the balanced EC expression was obtained using equation (5).

$$EC_{Vj} = EC_{Lj} \times P \quad (5)$$

where EC_{Vj} was the EC of j villages in Chongqing. EC_{Lj} was the EC of j type projects in the villages. P was the distribution coefficient of the project in the village. Since the consumption of energy was not a direct consumption but acted in the form of electrical energy through conversion, when calculating CEs, the loss of energy conversion process also needed to be included in CEs and was calculated as follows.

$$EC_{Gj} = PC + FC - NEU \quad (6)$$

where EC_{Gj} was the total EC value in the rural scenario. PC was the amount of loss in the energy conversion process. FC was the amount of consumption at the energy use end. NEU was the EC of non-CEs. The study classified and calculated the types of CE in rural areas of Chongqing to obtain the patterns of CE in the environment. The CE structure analysis of rural areas in Chongqing was obtained from the statistical yearbook (https://www.stats.gov.cn/sj/ndsj/). The study combined the energy structure analysis of rural areas in Chongqing and the CE calculation of industries and used BPNN to simulate the CE peak prediction model of rural areas in Chongqing. Moreover, with the help of the rural CE dataset in the statistical yearbook, the NN weights were trained and optimized to predict future CE peaks based on historical CE patterns.

Design of prediction path for PCE in rural areas of Chongqing based on optimized BP-GA

Peak CE means the change of energy structure and production mode in the environment [19]. Therefore, the attention to the CE problem is not only for environmental protection and energy saving, but also relates to the adjustment of the future development direction of the countryside [20]. To more accurately calculate the PCEs in rural areas of Chongqing, the study introduced genetic algorithm (GA) based on BPNN. The GA could calculate the OS for CEs under different energy consumption modes, while the BPNN efficiently extracted information features and converted data features through hidden layer steps. The BPNN could update the weight parameters of the hierarchy at any given moment through an iterative learning process based on data information. Furthermore, it could maintain a high level of accuracy in prediction throughout the data adjustment process. The BPNN updated the weight parameters of the layers at any time through iterative learning of the data information and maintained the data adjustment process in an adaptive manner to reach a highly accurate prediction capability. The activation process was expressed in equation (7) with sigmoid function used to optimize the NN's data transmission mechanism.

$$f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

where $f(x)$ was the activation function. x was the input values (IV). To train the accuracy and generalization of the NN, the dataset was selected for the process learning of the NN. The set of IVs of the dataset was shown in equation (8).

$$x(k) = (x_1(k), x_2(k), \ldots, x_n(k)) \tag{8}$$

where $x(k)$ was the aggregate function of the IVs. k was the selected data group. n was the input data sets. The corresponding output expectation relative to the IVs was shown in equation (9).

$$d_o(k) = (d_1(k), d_2(k), \ldots, d_n(k)) \tag{9}$$

where $d_o(k)$ was the set of desired output values. The transmission process of the NN was in terms of neurons. The input of the corresponding HL neuron was represented in equation (10).

$$hf_i(k) = \sum_{i=1}^{n} w_{ih} x_i(k) - a_i \tag{10}$$

where hf_i was the input data vector of the HL neuron. w_{ih} was the weight coefficient from the input layer to the HL. a_i was the bias value of the current layer. According to the number of neurons inside the HL, the neuron output value of each node of the HL could be calculated as follows.

$$ho_i(k) = f(hf_i(k)) \tag{11}$$

where ho_i was the output data vector of the HL neuron. The result arriving at the output layer (OL) according to the multi-layer pass of the HL was shown in equation (12).

$$yf_j(k) = \sum_{i=1}^{l} w_{ho} ho_i(k) - b_j \tag{12}$$

where yf_j was the current reception result of the OL. w_{ho} was the neuron transfer weight coefficients between HLs. b_j was the bias function between the HLs. l was the nodes in the HL. The predicted output was obtained after processing in the OL as equation (13).

$$yo_j(k) = f(yf_j(k)) \tag{13}$$

where yo_j was the prediction output result. The prediction result (PR) after cascade transfer was compared with the real value to get the actual error value. The step-by-step update of the weights was completed by back propagating the error. The PCE prediction in the rural areas of Chongqing was done using the best possible combination of BPNN and GA. The flowchart of the research algorithm was shown in Figure 1. The BP algorithm was suitable for the transfer process of the model, which cumulatively optimized the model prediction performance through its own iterative learning path. The advantage of GA relied on the search ability of the process with OS judgment. Therefore, the GA was used to calculate the update of weights and threshold judgment in the NN. In the research model, the constituent length of the transfer process was calculated in equation (14).

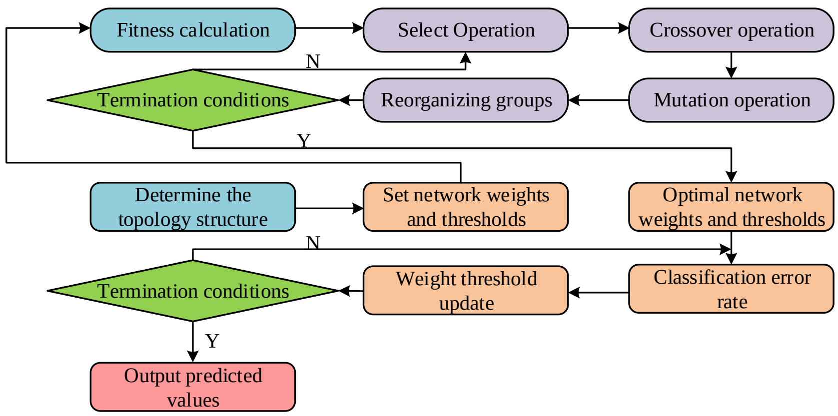

Figure 1. Flowchart of BP-GA process.

$$s = n_l \times l + l + l \times m + m \quad (14)$$

where s was the combined coding length. n_l was the nodes in the OL. m was the nodes in the OL. GA achieved the update of individuals by variation calculation as shown below.

$$f(g) = r_1 \bullet (1 - \frac{g}{G_{max}}) \quad (15)$$

where $f(g)$ was the variation function. $\bullet$ denoted the mutation calculation. $G_{\max}$ was the maximum number of evolutionary times in the process. r_1 was the selected random number. g was the number of iterations of GA. The results of individual variation after GA optimization were shown in equation (16).

$$\begin{cases} X_{ij}^{t+1} = X_{ij}^{t+1} + (X_{ij}^{t+1} + X_{\max}) \bullet f(g) & r < 0.5 \\ X_{ij}^{t+1} = (X_{\min} - X_{ij}^{t+1}) \bullet f(g) & r > 0.5 \end{cases} \quad (16)$$

where X_{ij}^{t+1} was the mutation result of the gene fragment. $X_{\max}$ was the maximum value of the gene fragment. $X_{\min}$ was the minimum fetch value of the gene fragment. r was the value of the random number. To enhance the efficiency of the model's optimal pathway exploration in CE calculations, the local and then global exploration steps were carried out in the form of interval calculations.

Datasets and computing instruments

To ascertain the efficacy of the CE peak prediction model, agricultural CE datasets from 2005 to 2020 were selected from the FAOSTAT (http://faostat3.fao.org/home/ index.html), CEADs (https://www.ceads.net.cn/ data/), MEIC (http://meicmodel.org/?page_id =560), and Carbon Monitor (http://www.carbonmonitor.org.cn) databases for analysis. After training the research model, the Chongqing regional CEs data were selected from the MEIC and Carbon Monitor datasets to divide the test set. Test set A contained CE data from rural agriculture in Chongqing, while test set B contained CE data from rural animal husbandry in Chongqing. The ratio of training data to test data for the model simulation validation was 10:1. The testing process employed MATLAB (https://www.mathworks.com/products/matlab.html) as the modeling and simulation platform. Intel Core i9-13900K computer with NVIDIA GeForce GTX 1060 graphics card and M393A4k4B1-CRC memory model was used as the hardware in this study. The research model first analyzed the current situation of CEs in rural areas of Chongqing and classified and calculated according to the current energy use. Then, the optimization measures of energy structure were planned and the CE ratio under the new energy structure was calculated based on the current state of technological development. The study analyzed the optimization results by comparing the historical CE values with the predicted CE

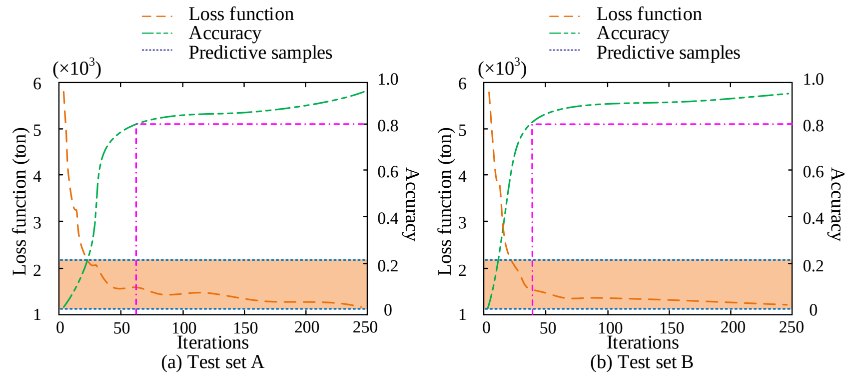

Figure 2. Performance testing in the test set.

values after the structural update and completed the prediction of PCEs based on the analysis results. The research process was based on the simultaneous calculation of EC and carbon neutrality and statistics on the types of EC and transformation patterns. Combining the two algorithms yielded the GA-BP model, which was used to forecast the CE changes.

Results

Performance test of carbon peaking prediction model based on optimized neural network algorithm with GA

To validate the planning performance and prediction effect of the carbon peak path study model, this study set the learning rate of the model to 0.01 and the average absolute percentage error to 18%. There were 250 iterations in the algorithm with a population size of 10. The model's loss function (LF) variation and PA demonstrated that, as the iterations increased, the LF of the BP-GA model in test set A exhibited a declining trend (Figure 2a). When the number of iterations went beyond 25, the LF still exhibited a declining trend, but the rate of drop slowed down. The PA of the research model in test set A showed an increasing trend with the number of iterations and reached more than 80% when the number of iterations reached 60. In test set B, the LF of the research model changed in line with that of test set A (Figure 2b). After 30 iterations, the research model's LF essentially converged, and the pace of reduction slowed down. The PA of the BP-GA model in test set B also tended to increase with the number of iterations. The PA of the proposed model reached more than 80% when the number of iterations reached 40, which indicated that the BP-GA model had a stable trend of LF change and good convergence in different test sets. To further compare the predictive performance of the model, the PSO algorithm was used to compare its performance with the research model [21]. 30 samples were selected to verify the predictive performance of the model. The PRs of the improved BP-GA model were basically consistent with the actual values of the samples (Figure 3a). The change curves predicted by the model highly overlapped with the actual change curves of the samples. The PR of the model was 4.08×10^3 when the actual result of the sample was 4.19×10^3. The sample error rate of the research model in the test was only 0.5%. The PSO algorithm's PRs for the samples were partially inconsistent with the actual results, but the trend direction of the predicted curve changes was consistent with the actual sample curve changes (Figure 3b). The PSO algorithm's sample error rate in the test was 3.4%, which indicated that the PA of the improved BP-GA model for the current sample was higher than that of the PSO algorithm. However, due to the small samples in the test, the prediction error rate of both groups of methods performed low, and the error value was maintained within 5%. To reflect the adaptation change of the research

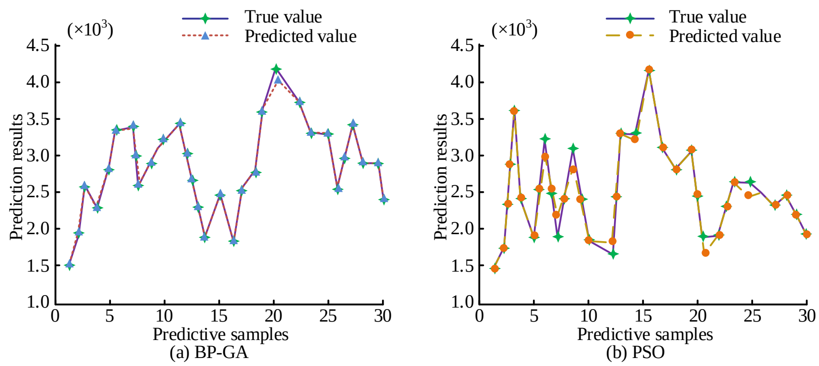

Figure 3. Comparison of model prediction performance.

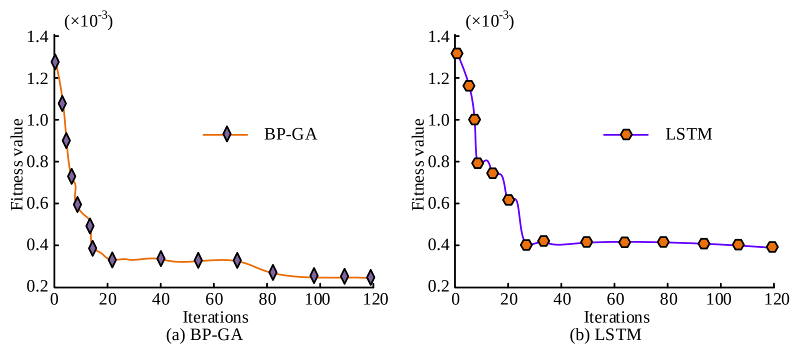

Figure 4. Comparison of model fitness change curves.

model in the scene, the algorithm iterations were set to 120. The study compared the introduction of LSTM algorithm with the improved BP-GA model and obtained the fitness change curve [22]. The fitness value of the improved BP-GA model was decreasing with the iterations. The fitness of the research model before the iterations reached 20 decreased rapidly, and the fitness value fell to 0.36 × 10^{-3}. After reaching 20 iterations, the fitness of the research model started to converge, showing a slow decreasing trend, and the final fitness value was 0.22 × 10^{-3} (Figure 4a). The fitness value of the LSTM algorithm was also decreasing with the increase of iterations. However, the rate of decrease in the fitness of the LSTM algorithm started to slow down after 8 iterations. When the iterations reached 25, the fitness decreased to 0.39 × 10^{-3}. The change in the fitness value of the LSTM algorithm basically stabilized after the iterations up to 25. When the algorithm completed the iterations, the final fitness value behaved as 0.38 × 10^{-3} (Figure 4b). The fitness value of the improved BP-GA model was always in a decreasing trend in 120 iterations of change, while the fitness value of the LSTM algorithm no longer decreased after 25 iterations. The results suggested that the proposed model's optimization effect was noticeably superior to that of the LSTM approach, and it could avoid the algorithm's optimization bottleneck.

Application effect test of the improved BP-GA based carbon peak path exploration model

To test the effect of the improved BP-GA model in the application of carbon peak pathway planning, the study set the natural population growth rate in rural area of Chongqing, China as 3.09%, while coal consumption, natural gas consumption, and new energy supply were set at 17%, 23%, and 16% to account for the total EC, respectively, which were consistent with PSO

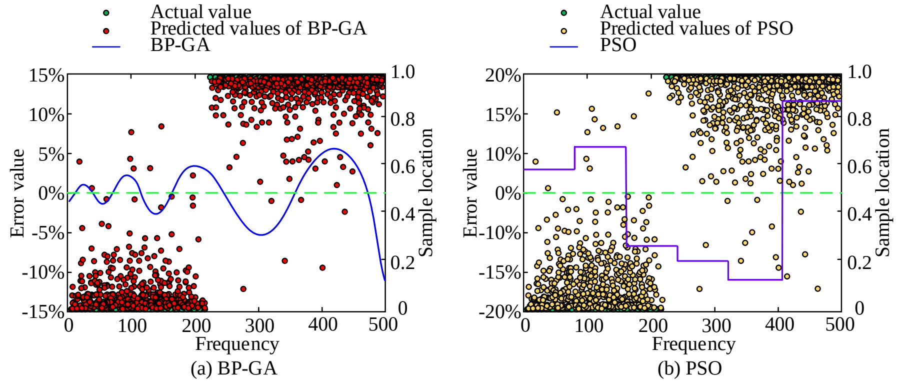

Figure 5. Model prediction performance and error variation.

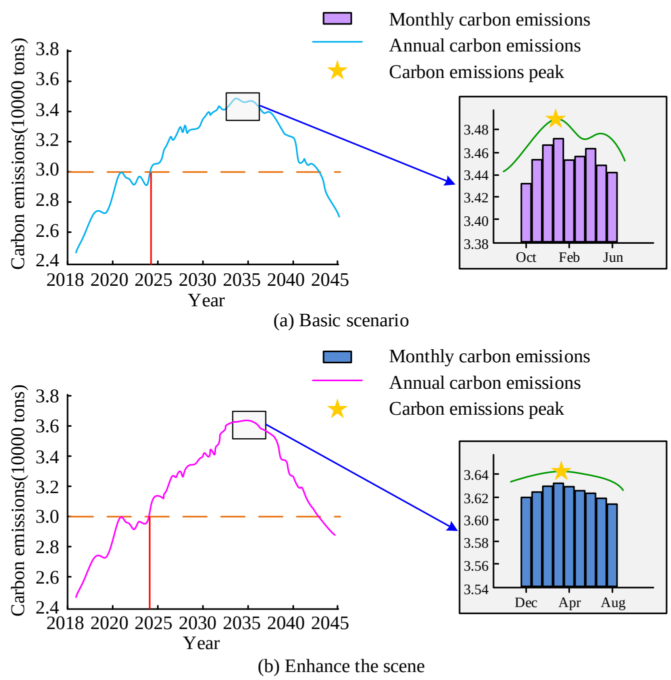

Figure 6. Prediction of PCE in Chongqing rural areas.

comparison model. The test was performed to detect the prediction effect of the proposed model in the practical application and the change of the error value. The results showed that the enhanced BP-GA model's predicted value placements in the scene were centrally near to the actual value positions (Figure 5a). Only a small number of the studied models had predicted value locations far from the true values. The overall PA of the model was 87.61%. The prediction error of the improved BP-GA model for real time was 1.2% - 11.8%. Most of the predicted value positions of the PSO algorithm in the scenario were close to the true value positions, but some of the predicted values were dispersed towards the center (Figure 5b). The overall prediction value accuracy of the statistical PSO algorithm in the scenario was 75.42%, and the prediction error in real time was 6.4% - 17.2%. The results showed that the proposed model had better prediction in the applied scenarios and 12.19% higher accuracy than that

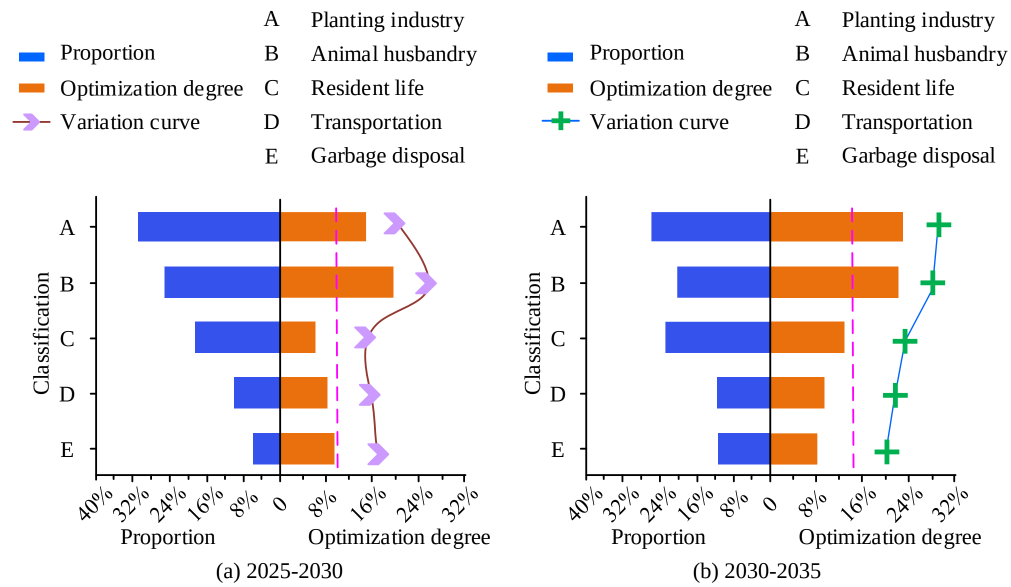

Figure 7. Changes in carbon emissions from rural industrial structure in Chongqing.

of the PSO algorithm. The performance of the proposed model was more stable from the performance of the prediction error and more accurate in judging the changes in CEs influenced by multiple factors. To test the effect of the model on the CE problem in Chongqing's rural areas, the outcomes of the CE changes predicted by the model under the two sets of scenarios were calculated. The results showed that the CEs in Chongqing rural areas predicted by the improved BP-GA model under the base scenario demonstrated an upward trend from 2024 to 2034 and reached the PCE in January 2034. In addition, the proposed model predicted that the CEs in Chongqing rural areas would increase from 29.85 million tons to 34.72 million tons during the period of 2024 – 2034 (Figure 6a). The trend of CEs in Chongqing rural areas under the enhanced scenario was consistent with the base scenario, reaching the PCE in March 2034. The proposed model predicted that the CEs of Chongqing rural areas in the enhanced scenario would increase from 29.85 million tons to 36.31 million tons during the period of 2024 - 2035. The results suggested that the model predicted CEs in Chongqing rural areas would peak at a similar time under both sets of scenarios. However, the peak CE in the enhanced scenario was 4.8% higher than that in the base scenario. The changes in CEs from the industrial structure in Chongqing rural areas were analyzed according to the predicted paths. The average share of CEs from cultivation in total EC between 2025 - 2030 was 32.09% based on the predictive analysis of the BP-GA model. The CE share of livestock, residential life, transportation mode, and waste disposal were 26.76%, 18.25%, 10.91%, and 6.78% of CEs, respectively. Moreover, animal husbandry had the largest decrease in CEs among rural industries with an average decrease of 19.12% (Figure 7a). The improved BP-GA model predicted that the CEs between 2030 and 2035 would still be the highest in the plantation industry, but the share of CEs from residential life and waste disposal process would increase (Figure 7b). The change of the decrease of each industry showed that the decrease of CE of plantation industry in the current time period was increased by 8.19%, and the decrease of CE of residential life was increased by 6.47%, which indicated that the main optimization targets of Chongqing rural industries in the process of reaching the PCE were planting and animal husbandry. The proposed model could effectively plan and adjust the CEs in the agricultural production process.

Discussion

To optimize the industrial CE problem in the rural environment of Chongqing, China, this research proposed the optimization method of rural CE with the self-learning ability of NN and the decision algorithm of cross-variation. The research method calculated the current CEs of the allocated items with the material balance algorithm and planned the emission reduction promotion projects of the industries according to the optimizable options. The study also calculated the optimal weights of the NN with the exploration ability of the GA and adjusted the applicability of the NN by back propagating the error of the PRs. The results showed that the prediction error rate of the research model was 0.5% for the tested small-volume samples, which was 2.9% lower than the error rate of the PRs of the PSO algorithm. After increasing the number of model predictions, the overall PA of the model was 87.61%, which was 12.19% higher than the accuracy of the PSO algorithm. The results suggested that the prediction performance of the research model was good during the testing process. According to the prediction of CE peak in rural areas of Chongqing under two sets of industrial optimization scenarios, the carbon peak time after industrial structure optimization was in 2035. However, under extended scenarios, the efficiency of structural optimization in this area might not be as expected. Therefore, the CE problem of regional industries was more severe, and the predicted CE peak was higher. Based on the analysis of changes in CEs from industrial structure, the optimization process led to a greater optimization of CEs in planting and animal husbandry, reducing industrial CEs. This study demonstrated that the optimization of CE structure in rural areas of Chongqing was more efficient in terms of planting and animal husbandry. Based on the analysis of the reasons, the GA data mutation optimized the model's adaptability to diverse data and improved the model's PA for rural data in Chongqing. Meanwhile, the BPNN model combined with GA improved the data analysis ability of rural CE structure. Therefore, it could obtain more reliable PRs based on strengthened preset scenarios. Liu *et al*. predicted the total CEs of Chongqing based on gray relational analysis and particle swarm optimization algorithm, but the prediction effect of industrial CEs in rural environments was not satisfied [21]. Compared with this method, the research model had a more stable prediction effect and higher PA for rural environments. Ahmed *et al*. used the LSTM algorithm to predict the growth of CEs in coal-consuming countries with multiple populations, which effectively validated the application effect of industrial structure transformation on reducing CEs [22]. However, this method lacked the analysis of China's rural industrial structure, while the research model provided targeted analysis of regional issues to improve the prediction of CEs from rural industries in Chongqing, China. Since the research model's exploration of the path for the peak of rural CEs depended on regular changes in CEs, data predictions for future CEs might be affected by irregular factors such as sudden temperature fluctuations. It was thus recommended that the scope of model data collection should be expanded in the future, and that the predictive performance of the model should be further optimized by combining data with irregular factors, which would facilitate the appropriate exploration and planning of CE peak paths for a greater number of scenarios.

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